Automatic Aneurysm Segmentation via 3D U-Net Ensemble

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❑ Introduction:

Accurate segmentation of cerebral aneurysms is of great significance to allow for a longitudinal assessment of the development of suspicious aneurysms. To this end, this paper proposed an effective method ensembling several models based on 3D UNet to segment cerebral aneurysms. Specifically, we used group normalization in our models and trained them by Dice ranking loss. Our methods achieved the promising performance in the ADAM Challenge.

❑ Method:

1) Data Preprocessing

- **Spacing Normalization**
  - ➢ resample images to the same voxel spacing
- **Intensity Normalization**
  - ➢ z-score normalization per modality
- **Cube Extraction**
  - ➢ 33% cubes must contain foreground pixels, 67% are random cropped
- **Data Augmentation**
  - ➢ Scaling: [0.7, 1.4]
  - ➢ Rotation: [-30°, 30°]
  - ➢ Gamma augmentation: $i\_new = i\_old^{\gamma}$, $\gamma \sim U(0.7, 1.5)$
  - ➢ Mirror

2) Network Architecture

The network architecture of the proposed framework is as below:

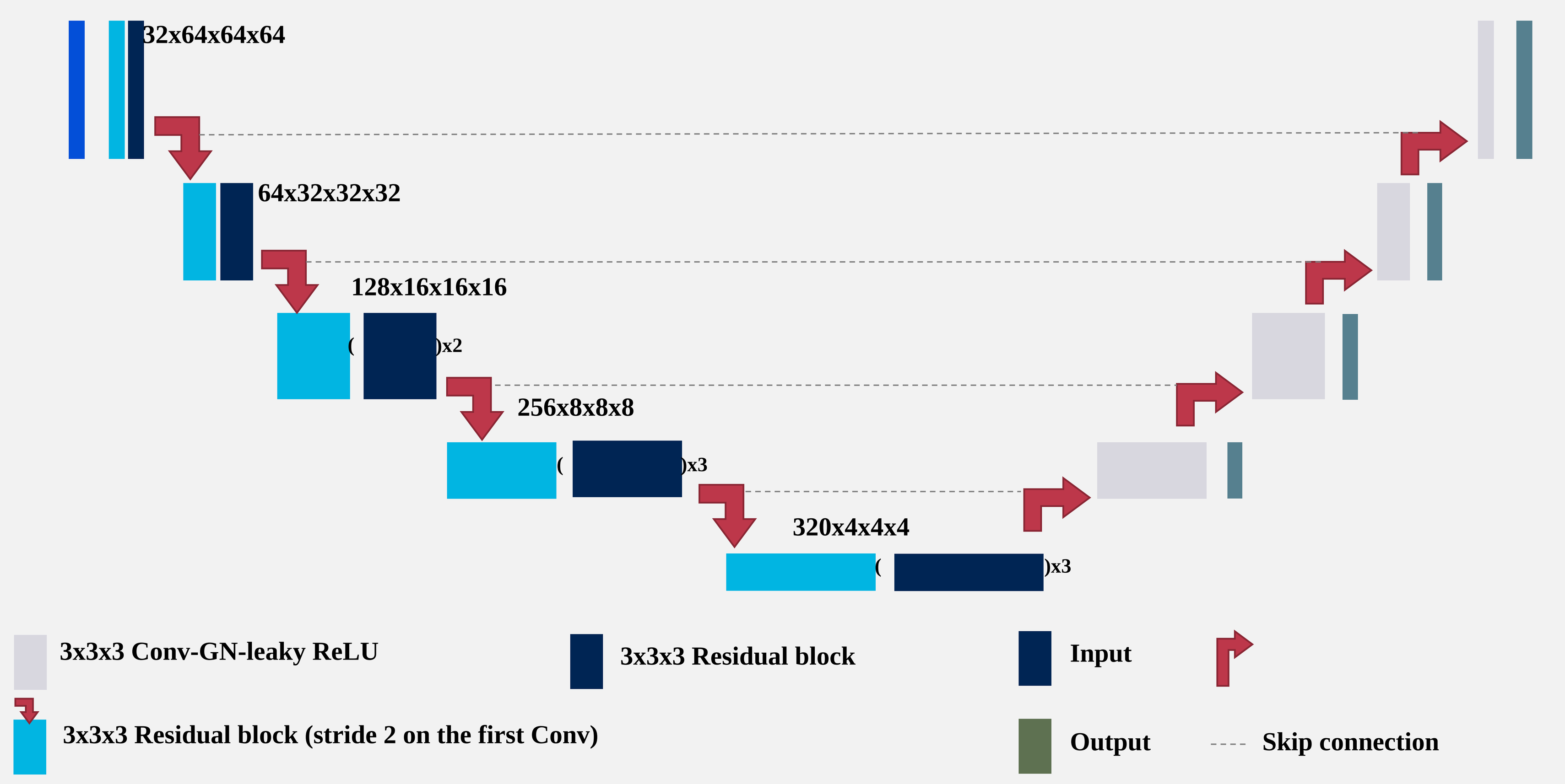


Figure 1: Architecture of the proposed network.

3) Network Training

The model is a 3D CNN similar to No New-Net. Compared to the original 3D U-Net, we made some small modification. first, Batch Normalization was replaced by Group Normalization; second, we used leaky ReLU instead of original ReLU; third, we used Dice ranking loss to improve the segmentation of small lesions.

This submission did not use any data other than the official training set. And the model was initialized randomly. Random patches of size 192 × 224 × 56 were sampled from the images and used for training with a batch size of 6. The Adam algorithm was used for optimization with an initial learning rate of 3*e*-4. We also used weight decay with 1*e*-5 and cosine annealing strategy. Specially, we trained our models with one modality input (TOF-MRA) and two modalities by concatenating them in the feature dimension, respectively. Also We trained our model to predict only label 1 and both label 1 and label 2, respectively. The environments of the code are python3.6, Cuda10.1, Cudnn7.6, Pytorch 1.14.0, Nvidia Tesla V100.

4) Ensemble model

To improve the robustness of our model, an ensemble method was employed for the final segmentation. Predictions were made by four separate models and ensembled together with majority voting.

❑ Experimental Results:

Table 1: performance comparison between different input and out class.

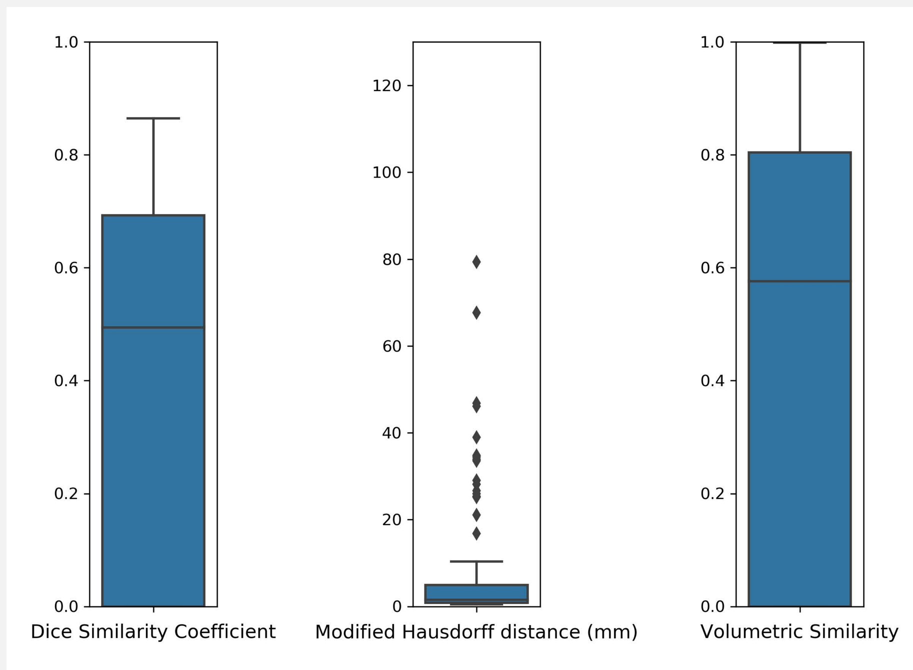
Method		Dice（%）
Modality	**Fore-ground class**	**Fold 2**
TOF-MRA	One	57.36
TOF-MRA	Two	61.35
TOF-MRA & Structural MRI	One	55.12
TOF-MRA & Structural MRI	Two	59.06

Team: joker	Task 1 Rank: 0.06	Task 1 Place: 2 nd
	Task 2 Rank: 0.02	Task 2 Place: 2 nd

(lower rank is better)

Task 1	False Positives	Sensitivity
Average	0.16	0.63
Rank	0.01	0.11

Task 2	Dice Coefficient	Modified Hausdorff Distance (mm)	Volumetric Similarity
Average	0.4	8.67	0.48
Rank	0.02	0	0.04



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